The Beyond 5G (B5G) Era of Next-Generation Digital Networks: Preliminary Study of a Task-Technology Fit (TTF) Model for Remote Robotic Surgery Applications

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Abstract: The coming Beyond 5G (B5G) era could mark a paradigm shift towards user-centric Quality of Experience (QoE) centred network architectures. The infusion of QoE user requirements into network architectures will be crucial for future ultra-reliable, ultra-low latency haptic-enabled Internet applications. One such application will be the mission-critical use case of remote (tele-haptic) robotic surgery, signifying a transition towards skillset delivery networks that will augment user task performance experience. In extending traditional Quality of Service (QoS)-oriented networks to user focused QoE and with it, Quality of Task (QoT) components, human users in a global control loop (such as robotic surgeons) will be capable of true-to-life immersive remote task performance through the manipulation of objects in real-time, and of transcending geographical distance. In this preliminary study using data elicited from 20 practising robotic surgeons (n = 20), we examine the emergence of a future B5G network and haptic-enabled Internet of Skills (IoS) architecture, applied to the task-sensitive mission-critical use case of remote (tele-haptic) robotic surgery. We conceptualise and demonstrate the use of non-linear Task-Technology Fit (TTF) predictive modelling to empirically assess this futuristic use case, and in doing so, provide a novel QoE/QoT perspective of future B5G communication networks.

1 INTRODUCTION

The emergence of Beyond 5G (B5G) networks such as 6G networks (Giordani et al., 2020) and quantum communication networks (Bassoli et al., 2021) offer much promise. These digital networks of the future will transcend the limits of current 5G network technologies (Nawaz et al., 2019). Originally, the traditional Internet was envisaged as a global computer network, signifying a paradigm shift in 20th century economies (Shapiro & Varian, 1999). This era brought forth the revolutionary Mobile Internet, connecting billions of devices and computers, disrupting whole 21st century economies and industries (Dohler, 2018). In the present day, the Internet of Things (IoT), predicted to tether trillions of smart devices and positioned to redefine industries of the coming decade, has come to the fore. These Internets will, however, be overtaken by the emergence of a haptic-enabled Internet whereby highly responsive secure networks will support the rendition of real-time haptic impulses remotely. This would amplify the capacities of the IoT by introducing a new element to human-machine interaction via the development of immersive real-time communications technologies (Pierucci, 2015). In future Internets, haptics will take the form of two key attributes: the transmission of touch and actuation in real-time will extend traditional audio-visual feedback of current systems via the support of both tactile (cutaneous) and kinaesthetic modalities. Firstly, the tactile (cutaneous) modality would render data on the dimensions of surface, texture, and friction. Secondly, the kinaesthetic modality would relay data on force, torque, position, and velocity

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dimensions. With these transmission modes, human users would be linked to remote environments with more immersion. The sensations of sight and sound augmented by audio-visual rendition and the transmission of haptic impulses would be bi-directional. Hence, touch would be detected by imposing motion on an environment with feeling rendered through a distortion or reactionary force. Haptics will become critical to future Internet architectures with the emergence of the B5G era. A future haptic-enabled Internet will shift conventional Quality of Service (QoS) performance-related indicators towards more dynamic, interactive and human-user-centred Quality of Experience (QoE) and Quality of Task (QoT) considerations (Gatara & Mzyece, 2023).

2 REMOTE ROBOTIC SURGERY APPLICATIONS FOR TELE-HAPTIC SURGICAL TASK PERFORMANCE

B5G networks will enable the future Internet of Skills (IoS) (Dohler, 2018). The performance of real-time tele-haptic robotic surgery tasks is a mission-critical application that leverages the ultra-reliable and ultra-low latency requirements that will become synonymous with B5G networks of the future. To envision the connection between QoS, QoT, and QoE components of a haptic-enabled IoS architecture, we present this robotic telesurgery use case in Figure 1.

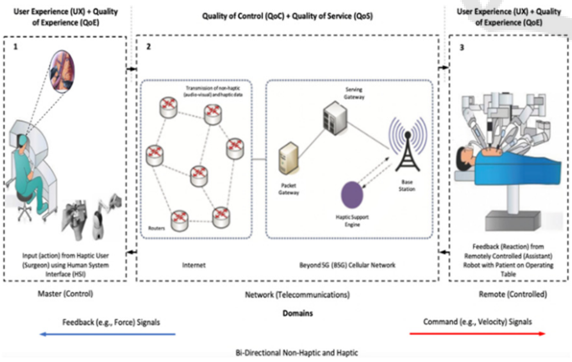

Figure 1: Haptic-Enabled Internet of Skills (IoS) for Tele-Haptic Surgical Task Performance in Beyond 5G (B5G) Networks.

In this scenario, a robotic surgeon with the requisite expertise will be the Human-in-the-Loop (HITL) supported to perform tele-haptic surgery tasks. A master (control) and assistant surgical robot in a remote-controlled environment must be connected through a reliable high-speed communication network to render real-time control commands and multi-modal sensory data. This enhanced form of tele-haptic surgery will require high-precision manipulation and meet stringent latency, jitter, and packet-loss metrics. Therefore, future B5G networks will be expected to more consistently and reliably ensure the ultra-low latency and ultra-reliable characteristics necessary for seamless two-way haptic feedback. On this basis, in a future Internet, surgeons will be able to extend their physical skillsets over remote geographical distances via a B5G-supported telecommunications network. Consequently, current shortages of surgeons and high-quality surgical care, and long-distance limitations in travel would be greatly reduced. Furthermore, surgical precision and patient safety would be enhanced.

3 TASK-TECHNOLOGY FIT (TTF) THEORY AND PREDICTVE MODELLING FOR REMOTE ROBOTIC SURGERY APPLICATIONS

The theoretical construct of Task-Technology Fit (TTF) denotes the measurement of the degree to which the functional capacity of a tool or system is adequate for user needs or requirements (Goodhue, 1995; Dishaw & Strong, 1998). The theory of TTF can be traced to the earlier theories of Cognitive Fit, which suggests that effective, efficient problem solving relies on matching characteristics of problem representation and problem task (Vessey, 1991, 1994; Vessey & Galleta, 1991), and Task-System Fit, which is "the fit between task requirements and the functionality of the IS [Information Systems] environment" (Goodhue, 1992). A TTF conceptual model of a haptic-enabled IoS is proposed and illustrated in Figure 2 (Gatara et al., 2021).

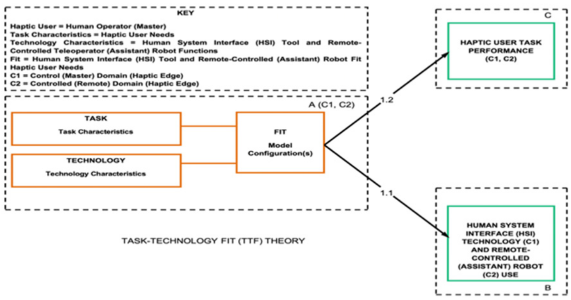

Figure 2: Conceptual Task-Technology Fit (TTF) Model for Quality of Experience (QoE) with Quality of Task (QoT) Perspective of a Haptic-Enabled Internet of Skills.

The model in Figure 2 links task and technology characteristics in (i) the master (control) domain and (ii) the remote (controlled) domains. First, task characteristics denote the most critical needs of the human technology user. User needs can be specified as surgeons' most critical task demands in remote robotic surgery (tele-haptic surgical task performance).

To perform critical minimally invasive robotic surgery tasks (grasping, palpation, and incision), the user (surgeon) concurrently uses (i) a manipulator (hand controller) and touch haptic device (remote controller) as part of the Human System Interface (HSI) in the master (control) domain and (ii) manipulators (grasper, palpation probe, and end-effector tip (cutter)) in the remote (controlled) domain.

4 INSTRUMENT SCALE (ITEM) MEASURES FOR TASK-TECHNOLOGY FIT (TTF) MODEL VARIABLES

The Task-Technology Fit (TTF) model developed for this research links task and technology characteristics in (i) the master (control) domain and (ii) the remote (controlled) domains.

First, task characteristics denote the most critical needs of the human technology user (Nance, 1992). User needs can be specified as surgeons' most critical task demands in remote robotic surgery (tele-haptic surgical task performance). For example, these include (i) control movement (motion) of remote assistant robotic arms (telemanipulators) e.g. to manipulate a needle drive (end effector) tool (surgical instrument) with wrist-like movements (1A), (ii) visualisation (with magnification) of the operative (surgical) field (area) e.g. for immersive stereoscopic view and endoscopic three-dimensional (3-D) High-Definition (HD) imaging (2A), and (iii) feeling and control of grasping force when operating on patient e.g. to displace tender organs (retraction) and soft tissue (clutching) (3A). The items used to measure these dimensions are detailed in Table 1.

Second, technology characteristics denote critical support functions for the most critical needs of the task performer (human user) (Dishaw et al., 2002). For example, there are critical corresponding support tools used by the surgeon including (i) interchangeable needle driver (end effector) tool (surgical instrument) attached to a lateral robotic arm with functional support i.e. movement up to 7 Degrees of Freedom (DoF) (1B), (ii) digitalstereoscopic camera (optic lens) with progressive magnification up to 15 times (15x) (2B), and (iii) interchangeable grasper tool (surgical instrument) attached to a lateral robotic arm with functional support i.e. laparoscopic forceps (5mm, 37cm) or fenestrated-grasper (3B). These identified corresponding task (user need) and technology (support function) characteristics (A and B pairs) will be measured using five seven (7)-point Likert measures on a scale from 1 (= to an extremely small extent) to 7 (= to an extremely large extent) (Yang et al., 2013). The items used to measure these dimensions are detailed in Table 2.

Table 1: Measurement Items for the Task (Characteristics) Construct (TC).

Variable	Scale Item	Source
TC 1A	Control movement (motion) of remote assistant robotic arms (telemanipulators) e.g. to manipulate a needle driver (end effector) tool (surgical instrument) with wrist-like movements.	Saracino et al. (2019), Yang et al. (2013)
TC 2A	Visualisation (with magnification) of the operative (surgical) field (area) e.g. for immersive stereoscopic view and endoscopic 3-D HD imaging.	
TC 3A	Feel and control grasping force when operating on patient e.g. to displace tender organs (retraction) and soft tissue (clutching).	
TC 4A	Palpation manoeuvres when operating on patient e.g. to detect neoplastic lesions in solid organs (hollow viscus).	
TC 5A	Incision (dissection) when operating on patient e.g. to cut soft tissue without damaging embedded vessels and nerves.	
TC 6A	Suturing when operating on patient e.g. to insert needle (puncture tissue), loop the suture thread (stitch), and tie the knot.	
TC 7A	Feel and reproduce true-to-life (realistic) haptic feedback when operating on patient e.g. to sense kinaesthetic (force/joint-related) and vibrotactile (cutaneous/skin-related) sensations.	

Table 2: Measurement Items for the Technology (Characteristics) Construct (TC).

Variable	Scale Item	Source
TC 1B	Control movement (motion) of remote assistant robotic arms (telemanipulators) e.g. via interchangeable needle drive (end effector) tool (surgical instrument) attached to lateral robotic arm with functional support i.e. movement up to 7 DoF.	Saracino et al. (2019), Yang et al. (2013)
TC 2B	Visualisation (with magnification) of the operative (surgical) field (area) e.g. digital stereo scoping camera (optic lens) attached to lateral robotic arm with functional support i.e. progressive magnification up to 15x.	
TC 3B	Feel and control grasping force when operating on patient e.g. Feel and control grasping force when operating on patient e.g. via interchangeable grasper tool (surgical instrument) attached to lateral robotic arm with functional support i.e. laparoscopic forceps (5mm, 37cm) or fenestrated grasper.	
TC 4B	Palpation manoeuvres when operating on patient e.g. via interchangeable laparoscopic/ultrasound probe tool (surgical instrument) attached to lateral robotic arm with functional support i.e. single-use and disposable with cross-section of less than 15 x 10 mm (diameter of 5 to 12 mm).	
TC 5B	Incision (dissection) when operating on patient e.g. via interchangeable end-effector tip (cutter) tool (surgical instrument) attached to lateral robotic arm i.e. sterile Carbon steel blade.	
TC 6B	Suturing when operating on patient e.g. via interchangeable needle driver (end-effector) tool (surgical instrument) attached to lateral robotic arm i.e. on CT-2 needles cut to 6 inches (for placement 0-Vicryl sutures).	
TC 7B	Feel and reproduce true-to-life (realistic) haptic feedback when operating on patient e.g. via force-sensing for multiple degrees of motion and force-awareness (combined) i.e. sigma.7 haptic (master) interface (kinaesthetic/vibrotactile feedback).	

The Use construct in Table 3 reflects the extent to which the task performer has come to depend on the technology tool and its support functions (Thompson et al., 1991; Igbaria et al., 1997; Junglas et al., 2009).

Table 3: Measurement Items for the Use (Dependence) Construct (UD).

Variable	Scale Item	Source
UD 1	I am very dependent on the use hand telemanipulators (finger controllers) to perform tasks using robotic arms (with attached surgical tools e.g. needle driver).	Saracino et al. (2019), Yang et al, (2013)
UD 2	My work is highly dependent on the use of hand telemanipulators (finger controllers) to perform tasks using robotic arms (with attached surgical tools e.g. probe).	
UD 3	The use of hand telemanipulators (finger controllers) to perform tasks using robotic arms (with attached surgical tools e.g. cutter) allows me to do more than would be possible without them.	

The User Performance construct in Table 4 on the other hand reflects the effectiveness, efficiency, and quality with which tasks are completed using the technology and its support functions to perform the most critical tasks needed (Hiltz & Johnson, 1990; Torkzadeh & Doll, 1999; Hou, 2012).

Five seven (7)-point Likert measures on a scale from 1 (= to an extremely small extent) to 7 (= to an extremely large extent) measure the Use and User Performance outcomes resulting from the “Fit” between Task and Technology characteristics depicted in Figure 3. The presence of this “Fit” is essential for optimal use and user performance (Nance, 1992).

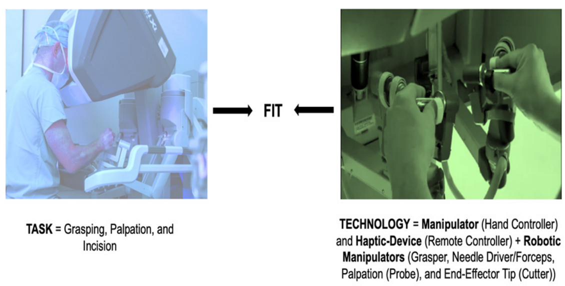

Figure 3: The Fit between Task and Technology Characteristics.

Thus, task-technology fit (TTF) is examined for its effects on Use and User Performance. The specific items used to measure these dimensions are detailed in Table 3 (above) and Table 4 (below).

Table 4: Measurement Items for the User Performance Construct (UP).

Variable	Scale Item	Source
UP 1	The hand telemanipulators (finger controllers) I use to control assistant robot and perform tasks using robotic arms (with attached surgical tools e.g. grasper) increases my productivity (easier task execution).	Saracino et al (2019), Yang et al (2013)
UP 2	The hand telemanipulators (finger controllers) I use to control assistant robot and perform tasks using robotic arms (with attached surgical tools e.g. probe) increases my productivity (time reduction in task completion).	
UP 3	The use of hand telemanipulators (finger controllers) to perform tasks using robotic arms (with attached surgical tools e.g. optic lens) decreases errors, increasing quality (capability enhancement in task execution).	

5 DATA COLLECTION AND DEMOGRAPHIC USER PROFILE OF RESPONDENTS

We collected preliminary data from 20 practising robotic surgeons (n = 20) via an electronic (online) survey designed to elicit user responses.

There were 19 male users (95%) and 1 female user (5%), mostly aged 51 years and above (40%) and between 46 and 50 years (35%). There were 18 right-handed dominant users (90%), plus 1 left-handed user (5%) and 1 ambidextrous user (5%). Additionally, 17 robotic surgeons (85%) were trained as Senior Faculty versus 3 as Junior Faculty (15%). Also, most of the robotic surgeons (65%) were reported to have undergone more than 10 simulator hours. Furthermore, 9 users (45%) were reported to have expert microsurgery experience, whereas 4 users (20%) were proficient. A further 11 users (55%) had expert robotic experience, whereas at least 7 robotic surgeons (35%) were expert-level laparoscopic practitioners. Notably, 5 users (25%) reported proficient videogame experience. The respondent user demographic profile for this preliminary cohort of practising robotic surgeons (n = 20) is provided in Table 5.

Table 5: Respondent User Demographic Profile (n = 20).

Variable(s)	Frequency	Percent (%)
Gender		
Male	19	95%
Female	1	5%
Total	20	100%
Missing	0	0%
Age		
36-40 years	3	15%
41-45 years	2	10%
46-50 years	7	35%
51 years and above	8	40%
Total	20	100%
Missing	0	0%
Hand Dominance		
Right-Handed	18	90%
Left-Handed	1	5%
Ambidextrous	1	5%
Total	20	100%
Missing	0	0%
Training Level		
Junior Faculty	3	15%
Senior Faculty	17	85%
Total	20	100%
Missing	0	0%
Simulator Hours		
None	2	10%
Less than 5 Hours	2	10%
6 – 10 Hours	3	15%
More than 10 Hours	13	65%
Total	20	100%
Missing	0	0%
Microsurgery Experience		
Novice	4	20%
Advanced Beginner	0	0%
Competent	3	15%
Proficient	4	20%
Expert	9	45%
Total	20	100%
Missing	0	0%
Robotic Experience		
Novice	1	5%
Advanced Beginner	1	5%
Competent	4	20%
Proficient	3	15%
Expert	11	55%
Total	20	100%
Missing	0	0%

Table 5: Respondent User Demographic Profile (n = 20) (cont.).

Variable(s)	Frequency	Percent (%)
Laparoscopic Experience		
Novice	6	30%
Advanced Beginner	1	5%
Competent	4	20%
Proficient	2	10%
Expert	7	35%
Total	20	100%
Missing	0	0%
Videogame Experience		
Novice	6	30%
Advanced Beginner	3	15%
Competent	4	20%
Proficient	5	25%
Expert	2	10%
Total	20	100%
Missing	0	0%

6 MEASUREMENT INSTRUMENT (CONSTRUCT) RELIABILITY AND VALIDITY

A Partial Least Squares Structural Equation Modelling (PLS-SEM) algorithm was run to estimate parameters of measurement model constructs. Confirmatory Factor Analysis (CFA) was conducted to test construct measures for their internal consistency, convergent, and discriminant validities. PLS-SEM functions efficiently with small sample sizes and attains high statistical power levels with small sample sizes even when the data is non-parametric or highly skewed (Hair et al., 2021), such as the preliminary sample (n = 20) used for preliminary nature of analysis in this study.

Composite Reliability (p_c) scores for the dimensions of Task, Technology, Use, and User Performance were satisfactory. Composite Reliability (p_c) ranged from 0.000 to 1.000, with higher values indicating higher levels of reliability (Hair et al., 2021). In more advanced research however, values between 0.700 and 0.900 are generally considered as satisfactory (Nunnally & Bernstein, 1994; Hair et al., 2021). The composite reliability scores for each latent Task, Technology, Use, and User Performance dimensions were found to be satisfactory (greater than 0.700). Thus, internal consistent reliability was established.

The descriptive statistics for these four dimensions are presented in Table 6.

Table 6: Descriptive Statistics.

Variable	Range	Mean	SD	Skewness	Kurtosis
Task	5.55	4.721	1.404	-0.189	0.127
Technology	6.00	4.173	1.578	0.073	0.014
Use	4.00	5.360	1.125	0.023	-0.502
User Performance	6.20	5.391	1.466	-1.095	2.038

Further, the Average Variance Extracted (AVE) values for each of the Task, Technology, Use, and User Performance constructs exceeded the prescribed threshold of 0.500 (Hair et al., 2021). Thus, results also reflected acceptable convergent validity.

The Task, Technology, Use, and User Performance constructs were also tested for their discriminant validity.

First, their indicator cross-loadings were evaluated. The outer loadings on all indicators on the associated construct did not score higher than any of its cross-loadings (correlations) on other constructs. Therefore, discriminant validity was established. Results of indicator cross-loadings are presented in Table 7.

Table 7: Cross-Loadings.

	Task	Technology	Use	User Performance
TaC1	**0.705**	0.383	0.216	-0.191
TaC2	**0.732**	0.587	0.407	-0.017
TaC3	**0.867**	0.732	0.253	0.210
TaC4	**0.611**	0.543	0.209	0.316
TaC5	**0.793**	0.511	0.358	0.170
TaC6	**0.817**	0.539	0.340	0.183
TaC7	**0.845**	0.778	0.283	0.101
TeC1	0.664	**0.618**	0.391	0.097
TeC2	0.602	**0.761**	0.444	0.194
TeC3	0.768	**0.875**	0.445	0.308
TeC4	0.661	**0.819**	0.308	0.476
TeC5	0.546	**0.818**	0.497	0.486
TeC6	0.584	**0.854**	0.549	0.324
TeC7	0.569	**0.835**	0.440	0.412
UDe1	0.429	0.285	**0.618**	0.245
UDe2	0.196	0.456	**0.855**	0.471
UDe3	0.410	0.556	**0.935**	0.518
UP1	0.141	0.273	0.565	**0.883**
UP2	0.214	0.474	0.484	**0.964**
UP3	0.203	0.045	0.224	**0.116**

Second, the Fornell-Larker Criterion was used to further establish discriminant validity. The square root of the AVE for each of the Task, Technology, Use, and User Performance variables was higher than correlations between these constructs and other latent variables. Therefore, discriminant validity was further established. Results of the Fornell-Larker criterion valuation with the square root of the reflective constructs' AVE on the diagonal, the means and standard deviations of study constructs, and correlations between the constructs in the off-diagonal positions, are presented in Table 8.

Table 8: Fornell-Larker Criterion Results.

	Mean (SD)	Task	Technology	Use	User Performance
Task	4.72 (1.40)	**0.771**			
Technology	4.17 (1.58)	0.769	**0.801**		
Use	5.36 (1.12)	0.398	0.552	**0.814**	
User Performance	5.39 (1.47)	0.181	0.431	0.529	**0.758**

Third, we further assessed discriminant validity using the Heterotrait-Monotrait (HTMT) ratio of correlations. Using HTMT as a criterion, all ratios were found to be below the conservative threshold value of 0.85, thus ascertaining the discriminant validity of the Task, Technology, Use, and User Performance measures. Results of the HTMT ratio values for all pairs of constructs in the measurement model are presented in Table 9.

Table 9: Heterotrait-Monotrait (HTMT) Ratio of Correlations.

	Task	Technology	Use	User Performance
Task				
Technology	0.868			
Use	0.517	0.646		
User Performance	0.409	0.478	0.778	

7 RESULTS: POLYNOMIAL REGRESSION AND RESPONSE SURFACE ANALYSIS

We modelled a relationship between Task and Technology characteristics as independent variables and Use and User Performance as dependent variables, respectively, as a non-linear function. This approach can have greater explanatory potential than traditional moderated regression analyses. Moreover, it can be used as an alternative method, as it outputs more precise information on combinations (interactions) of variables, beyond the results of more conventional moderator analyses.

First, polynomial regression (Edwards, 1993) was used to examine task and technology impacts on use and user performance.

Latent variable scores obtained from PLS-SEM analysis were used to compute Task (X) and Technology (Y) characteristics, their interaction (X*Y), and the quadratic terms (X^2, Y^2), in turn used to predict Use and User Performance outcomes (Z) as per the following polynomial equation [where b_n denotes the respective beta coefficients for corresponding X, Y, and Z terms, and e represents a random disturbance term]:

$$Z = b_0 + b_1X + b_2Y + b_3X^2 + b_4XY + b_5Y^2 + e \quad (1)$$

where:
Z = Use or User Performance
X = The Task
Y = The Technology

The above variables were centred at their midpoints i.e. '4' for 7-point Likert scales. Centring is recommended for polynomial regression analyses (Edwards, 1994). Further, Aiken and West (1991) suggested that centering reduces the likelihood of collinearity. With the above formula, coefficients for the terms X (b_1), Y (b_2), X^2 (b_3), XY (b_4) and Y^2 (b_5) were obtained.

Table 10: Polynomial Regression Results (Use).

Use		
Predictor	**Beta (β)**	**Standard Error**
Constant (b_0)	1.222***	0.336
Task (b_1X)	-0.215	0.580
Technology (b_2Y)	0.541	0.516
Task^2 (b_3X^2)	0.067	0.288
Task*Technology (b_4XY)	-0.074	0.171
Technology^2 (b_5Y^2)	0.074	0.359
$R^2 = 0.333$, $F = 1.399$		

Table 11: Polynomial Regression Results (User Performance).

User Performance		
Predictor	**Beta (β)**	**Standard Error**
Constant (b_0)	1.121***	0.376
Task (b_1X)	-1.046	0.649
Technology (b_2Y)	0.925	0.577
Task^2 (b_3X^2)	0.475	0.322
Task*Technology (b_4XY)	-0.254	0.402
Technology^2 (b_5Y^2)	0.072	0.192
$R^2 = 0.508$, $F = 2.896$		

Second, Response Surface Methodology (RSM) (Edwards, 2002) was used to plot three-dimensional (3D) surfaces relating Task and Technology to Use and User Performance.

Regression beta (β) coefficients resulting from equation (1) as presented in Tables 10 and 11 above, were used to estimate stationary points (X_0, Y_0), principal axes (p_{10}, p_{11}, p_{20}, p_{21}), and shapes along lines of congruence and incongruence (a_1, a_2, a_3, a_4). Surface values for prediction of Use and User Performance are shown in Tables 12 and 13.

Table 12: Response Surface Analysis Results (Use).

Use		
Stationary Point	X_0	-0.572 (-0.014)
	Y_0	-3.941 (-0.058)
First Principal Axis	Intercept (P_{10})	-4.570 (-0.064)
	Slope (P_{11})	-1.099 (-0.029)
	($-P_{10}/(1+P_{11})$)	-46.138 (-0.019)
Second Principal Axis	Intercept (P_{20})	-3.421 (-0.044)
	Slope (P_{21})	0.910 (0.030)
Shape Along Line of Congruence (Y = X)	Slope: a_1 ($b_1 + b_2$)	0.326 (0.639)
	Curvature: a_2 ($b_3 + b_4 + b_5$)	0.067 (0.350)
Shape Along Line of Incongruence (Y = -X)	Slope: a_3 ($b_1 - b_2$)	-0.756 (-0.463)
	Curvature: a_4 ($b_3 - b_4 + b_5$)	0.215 (0.097)

Table 13: Response Surface Analysis Results (User Performance).

User Performance		
Stationary Point	X_0	-1.167 (-0.003)
	Y_0	-8.481 -0.011)
First Principal Axis	Intercept (P_{10})	-8.818 (-0.010)
	Slope (P_{11})	-0.289 (-0.018)
	($-P_{10}/(1+P_{11})$)	-46.138 (-0.019)
Second Principal Axis	Intercept (P_{20})	-4.443 (-0.014)
	Slope (P_{21})	3.462 (0.012)
Shape Along Line of Congruence (Y = X)	Slope: a_1 ($b_1 + b_2$)	-0.121 (-0.177)
	Curvature: a_2 ($b_3 + b_4 + b_5$)	0.293 (1.124)
Shape Along Line of Incongruence (Y = -X)	Slope: a_3 ($b_1 - b_2$)	-1.971 (-0.993)
	Curvature: a_4 ($b_3 - b_4 + b_5$)	0.801 (0.234)

The response for the Task (X) and Technology (Y) predicting Use (Z) is shown in Figure 4.

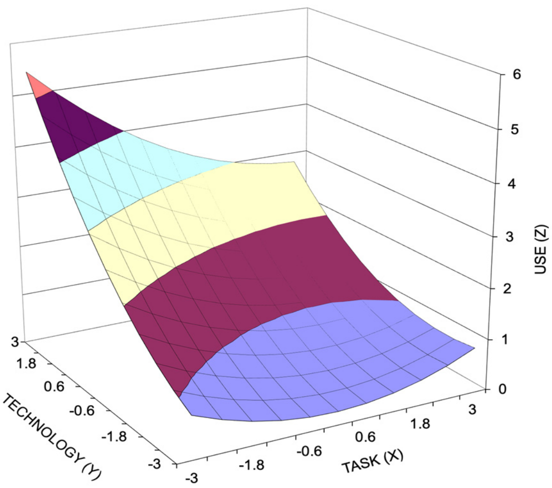

Figure 4: Response Surface for Task-Technology Fit (TTF) and Use.

The response surface for TTF effects on use was saddle-shaped (stationary point: X_0 = -0.572, Y_0 = -3.941). The first principal axis is not significantly different [t = -0.029 (P_{11}), t = -0.019 ($-P_{10}//P_{11}+1$)] from the line of congruence (Y = X). Thus, a perfect fit between the Task and Technology leads to maximal use. The upward slope along the line of congruence (Y = X) was negative but not significant. The curvature along the line of congruence (Y = X) was positive but not significant (a_2 = 0.293, t = 1.124), indicating that the relationship between TTF and use is linear. Therefore, the curvature along the line Y = X does not significantly change for use. The downward slope along the line of incongruence (Y = -X) was negative but not significant (a_3 = -1.971, t = -0.993). A lack of fit between the robotic surgery task and support tools leads to a decrease in use. The curvature along the line of incongruence (Y = -X) was positive but not significant (a_4 = 0.801, t = 0.234), further evidencing a linear association between TTF and use.

The response for the Task (X) and Technology (Y) predicting User Performance (Z) is shown in Figure 5.

The first principal axis is not significantly different [t = -0.018(p_{11}), t = -0.019(=p_{10}/p_{11+1})] from the line congruence (Y=X). Hence, a perfect fit between the task and technology leads to maximised user performance. The upward slope along the line of congruence (Y=X) is negative and not significant (a_1 = -0.121, t = -0.177). The curvature along the line

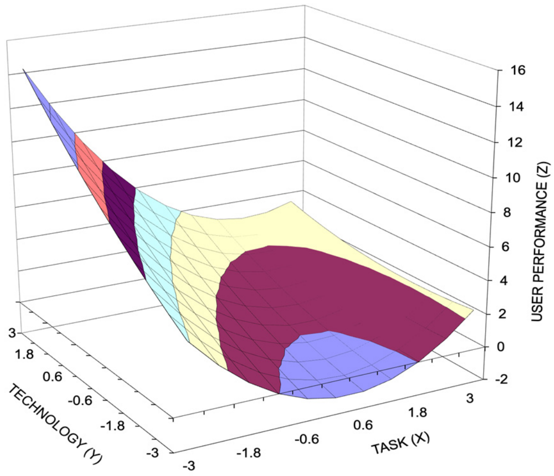

Figure 5: Response Surface for Task-Technology Fit (TTF) and User Performance.

of congruence (Y=X) was positive but not significant ($a_2 = 0.293$, $t = 1.124$), indicating that the relationship between TTF and user performance is linear. This indicates that the curvature along the line Y=X does not significantly change for user performance. The downward slope along the line of incongruence (Y=-X) was negative but not significant ($a_3 = -0.971$, $t = -0.993$). Hence, the lack of fit between the robotic surgery task and support tools leads to a decrease in user performance. The curvature along the line of incongruence (Y=-X) was positive but not significant ($a_4 = 0.801$, $t = 0.234$), further indicating a linear relationship between TTF and user performance. The curvature along the line Y=-X did not, therefore, change significantly for user performance.

The lateral shift (Atwater et al., 1998) in use and user performance, in the surface along and perpendicular to the line of congruence (Y = X) was determined using the following equation:

$$\text{Lateral Shift} = \frac{b_2 - b_1}{2\,(b_3 - b_4 + b_5)} \tag{2}$$

where:

b_1 = The beta value for Task

b_2 = The beta value for Technology

b_3 = The beta value for Task^2

b_4 = The beta value for Task*Technology

b_5 = The beta value for Technology^2

The lateral shift in use along the line of congruence (Y = X) was positive (1.758), indicating movement of approximately two units towards the region where functional support levels surpass user needs (Y > X). Here, the technology over-fits the task. Hence, when the robotic surgery task and support tool functions over-fit user needs, there is a sharp decline in robotic surgeons' dependence on use. Similarly, the lateral shift in user performance along the line of congruence (Y = X) was positive (1.230), indicating movement of approximately one unit toward the region where the robotic surgery task and support tool functions over-fit user needs. Thus, when the robotic surgery task and support tool functions over-fit user needs, there is a sharp decline in the effectiveness, efficiency, and quality, of robotic surgery task performance.

8 DISCUSSIONS

In this paper, we investigated the potential transition from technical system-oriented QoS to user-focused QoE and QoT Internet configurations of the future. We also explored the advent of an ultra-reliable and ultra-low-latency B5G network and haptic-enabled Internet. We applied this configuration to the use case of remote robotic surgical task performance (tele-haptic surgery applications) from the novel data-driven evidence-based QoE/QoT perspective of Task-Technology Fit (TTF) theory and predictive modelling.

The analysis of non-linear impacts on use and user performance represents a perspective of task-technology equilibrium. This mechanism enables more sophisticated and dynamic insights into the effectiveness of TTF, and is useful for observing the extent to which Information Technology (IT) functions affect tool use and user performance levels. Our findings show that when there is excessive functional support for robotic surgery tasks, there is an increasing likelihood of a lower dependence among users, on using the technology whereby they will more likely perceive that they deliver lower quality MIS robotic surgery task performance, with diminishing effectiveness and efficiency. This finding represents an "IT surplus", the supply of tool functions that could exceed user task requirements (Yang et al., 2013, p. 700). This is an extreme that signifies a misfit, which can adversely affect task productivity (Oh and Pinsonneault, 2007). Further, an overfit can result in declining information accessibility and processing performance, and has been attributed to an excess of support functions that can be termed as redundant (Jarvenpaa, 1989).

9 IMPLICATIONS FOR RESEARCH AND PRACTICE: THEORETICAL AND APPLIED CONTRIBUTIONS

From a more theoretical standpoint, an atomistic approach (Yang et al., 2013), said to involve the articulation and measurement of separate components (p. 712) was used. This novel approach signifies a more pragmatic, nuanced perspective of TTF impacts. It can be applied to subsequent research where the interaction effects of TTF warrant further investigation. Moreover, the detailed analysis of use and user performance effect differentials modelled using three-dimensional (3-D) surfaces represents richer insights into testing non-linear TTF.

From a more practical standpoint, the findings of this study can serve as key guidelines with which to enhance or reduce functional support related to robotic surgery support tool use and surgeon user performance. This can be an important benchmark with which robotic surgery support tool designers can calibrate the responsiveness of functional support to user task needs. Further, the findings indicate that excess or inadequate functional robotic surgery tool support for surgeons' user needs can lead to adverse use and user performance impacts. Hence, robotic surgery support tool designers must be acutely aware of these task-technology differentials to attain a state of congruence between supporting functions and robotic surgeon's needs.

10 CONCLUSIONS

In light of recent developments in ultra-reliable and ultra-low latency communications that will come to define next-generation digital networks, we conceptualised the emerging transition from QoS-centric content-delivery networks to QoE and QoT focused skillset-delivery network configurations that will typify closed-loop control architectures for haptic-enabled and B5G Internets. We offer the novel task-technology fit (TTF) conceptualisation and predictive modelling and empirical analysis perspective as a diagnostic tool. This vision of an Internet of the future will involve the task performer in a domain-specific technology user-focused context (remote setting) performing tasks as the human-in-the-loop (HITL), through immersive real-time human-to-machine/robot (H2M/R) interactions. Through this preliminary study, we examine the mission-critical user scenario of tele-haptic (remote) robotic surgery, expected to become a reality in the era of B5G. With a haptic-enabled Internet and B5G network to augment user skills, future robotic microsurgeons will be ably supported to perform seamless tele-haptic (remote) surgical tasks.

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REFERENCES

Aiken, L. S., & West, S. G. (1991). *Multiple Regression: Testing and Interpreting Interactions*. Sage Publications.

Atwater, L. E., Ostroff, C., Yammarino, F. J., & Fleenor, J. W. (1998). Self-Other Agreement: Does it Really Matter?. *Personnel Psychology*, 51(3), 577- 598.

Bassoli, R., Boche, H., Deppe, C., Ferrara, R., Fitzek, F. H. P., Janssen, G., & Saeedinaeeni, S. (2021). *Quantum Communication Networks*. Springer.

Dishaw, M. T., & Strong, D. M. (1998). Supporting Software Maintenance with Software Engineering Tools: A Computed Task-Technology Fit Analysis. *The Journal of Systems and Software*, 44(2), 107-120.

Dishaw, M. T., Strong, D. M., & Bandy, D. B. (2002). Extending the Task-Technology Fit Model with Self-Efficacy Constructs. *Proceedings of the 8th Americas Conference on Information Systems (AMCIS)*, August 9-11, 2002, Dallas, USA.

Dohler, M. (2018) The Future and Challenges of Communications – Toward a World Where 5G Enables Synchronised Reality and Internet of Skills. *Internet Technology Letters*, 1(2), 1-3.

Edwards, J. R. (1993). Problems with the Use of Profile Similarity Indices in the Study of Congruence in Organizational Research. *Personnel Psychology*, 46(3), 641-665.

Edwards, J. R. (1994). The Study of Congruence in Organizational Behaviour Research: Critique and a Proposal and a Proposed Alternative. *Organizational Behaviour and Human Decision Processes,* 58(1), 51-100.

Edwards, J. R. (2002). Alternatives to difference scores: Polynomial regression analysis and response surface methodology. In F. Drasgow & N. W. Schmitt (Eds.), *Measuring and Analyzing Behavior in Organizations: Advances in Measurement and Data Analysis* (pp. 350-400). Wiley.

Gatara, M. C., Mzyece, M., & Parekattil. S. J. (2021). Towards a Fifth (5th) Generation (5G) Network and Haptic-Enabled Internet for Remote Robotic Surgery:

A Task-Technology Fit (TTF) Model. *Proceedings of the 45th Meeting of the Wireless World Research Forum (WWRF)*, January 18-21, 2021, Kuala Lumpur, Malaysia.

Gatara, M. C., & Mzyece, M. (2023). From QoS to QoE plus QoT in Beyond 5G Networks. *Journal of Mobile Multimedia*, 19(1), 135-146.

Giordani, M., Polese, M., Mezzavilla, M., Rangan, S., & Zorzi, M. (2020). Toward 6G Networks: Use Cases and Technologies. *IEEE Communications Magazine*, 58(3), 55-61.

Goodhue, D. L. (1992). User Evaluations of MIS Success: What are we Really Measuring?. *Proceedings of the 25th Hawaii International Conference on Systems Sciences (HICSS)*, January 7-10, 1992, Hawaii, USA.

Goodhue, D. L. (1995). Understanding User Evaluations of Information Systems. *Management Science*, 41(12), 1827-1844.

Hair, J. F., Jr., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage Publications.

Hiltz, S. R., & Johnson, K. (1990). User Satisfaction with Computer-Mediated Communication Systems. *Management Science*, 36(6), 739-764.

Hou, C.-K. (2012). Examining the Effects of User Satisfaction on System Usage and Individual Performance with Business Intelligence Systems: An Empirical Study of Taiwan's Electronics Industry. *International Journal of Information Management*, 32(6), 560-573.

Igbaria, M., Zinatelli, N., Cragg, P., & Cavaye, A. L. M. (1997). Personal Computing Acceptance in Small Firms: A Structural Equation Model. *MIS Quarterly*, 21(3), 279-305.

Jarvenpaa, S. L. (1989). The Effect of Task Demands and Graphical Format on Information Processing Strategies. *Management Science*, 35(3), 285-303.

Junglas, I., Abraham, C., & Ives, B. (2009). Mobile Technology at the Frontlines of Patient Care: Understanding Fit and Human Drives in Utilization Decisions and Performance. *Decision Support Systems*, 46(3), 634-647.

Nance, W. D. (1992). *Task/Technology Fit and Knowledge Worker Use of Information Technology: A Study of Auditors*. Ph.D. Dissertation, University of Minnesota, Minnesota, USA.

Nawaz, S. J., Sharma, S. K., Wyne, S., Patwary, M. N., & Asaduzzaman, M. (2019). Quantum Machine Learning for 6G Communication Networks: State-of-the-Art and Vision for the Future. *IEEE Access*, 7, 46317-46350.

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric Theory* (3rd ed.). McGraw-Hill.

Oh, W. and Pinsonneault, A. (2007). On the Assessment of the Strategic Value of Information Systems: Conceptual and Analytical Approaches. *MIS Quarterly*, 31(2), 239-265.

Pierucci, L. (2015). The Quality of Experience Perspective Toward 5G Technology. *IEEE Wireless Communications*, 22(4), 10-16.

Saracino, A., Deguet, A., Staderini, F., Boushaki, M. N., Cianchi, F., Menciassi, A., & Sinibaldi, E. (2019). Haptic Feedback in the da Vinci Research Kit (dVRK): A User Study Based on Grasping, Palpation, and Incision Tasks. *The International Journal of Medical Robotics and Computer Assisted Surgery*, 15(4), 1-13.

Shapiro, C., & Varian, H. R. (1999). *Information rules: A strategic guide to the network economy*. Harvard Business School Press.

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal Computing: Toward a Conceptual Model of Utilization. *MIS Quarterly*, 15(1), 125-143.

Torkzadeh, G., & Doll, W. J. (1999). The Development of a Tool for Measuring the Perceived Impact of Information Technology on Work. *Omega, The International Journal of Management Science*, 27(3), 327-339.

Vessey, I. (1991). Cognitive Fit: A Theory-Based Analysis of the Graphs Versus Tables Literature. *Decision Sciences*, 22(2), 219-240.

Vessey, I. (1994). The Effect of Information Presentation on Decision Making: A Cost-Benefit Analysis. *Information and Management*, 27(2), 103-119.

Vessey, I., & Galletta, D. (1991). Cognitive Fit: An Empirical Study of Information Acquisition. *Information Systems Research*, 2(1), 63-84.

Yang, H.-D., Kang, S., Oh, W., & Kim, M. S. (2013). Are All Fits Created Equal? A Nonlinear Perspective on Task-Technology Fit. *Journal of the Association for Information Systems*, 14(12), 694-721.